A Comparative Study of Recent Practices and Technologies in Advanced Driver Assistance System

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ABSTRACT
Road accidents present a pressing global public health concern particularly impacting low and middle-income countries like Bangladesh. Advanced Driver Assistance Systems (ADAS) can help in the reduction of risks at a significant level. There are few comprehensive reviews of different significant components of ADAS up to early 2021, highlighting strengths, weaknesses, and research gaps in this rapidly evolving field. This article offers a systematic review of high-quality research articles in the field, encompassing publications from March 2021 to December 2023. This review tends to give a clear and concise view of the key advancements in sensor technologies, machine learning techniques used in the system, qualitative assessment of the datasets available, popular performance metrics, and the projection of trends in the coming days. Cameras are found to be the most used sensor technology while working with ADAS. With the advancement of machine learning, the existing literature tends to use several benchmark models instead of sticking to one or more traditional ones. The existing datasets cover various weather scenarios, mostly sunny, rainy, and foggy weather. These datasets are mostly on urban roads and highways. Researchers tend to evaluate the performance of the systems using metrics that rely on confusion matrices. As per this study, it can be said that a completely real-time system is still a crying need. Due to the existence of a diverse range of road scenarios, a dataset covering all of them is not available. Future research can go in the direction of using hybrid sensor technology, focusing on versatile datasets, and using improved machine and deep learning technologies.

Keywords
Advanced Driver Assistance System, Road Safety, Machine Learning, Deep Learning.

1. INTRODUCTION
The World Health Organization (WHO) [1] estimates that 1.3 million individuals lose their lives in traffic accidents every year. More than 90% of traffic-related fatalities take place in countries with middle and low incomes. These accidents cost most countries 3% of their GDP. Road safety is one of the major concerns for middle and low-income countries as due to several avoidable reasons, roads there are getting dangerous for both drivers and pedestrians over the years. This resulted in a significant increase in the number of road accidents and casualties in the last 6-7 years. According to the 2021-22 annual report of Bangladesh Road Transport Authority (BRTA) [2], the damage to life is ever increasing from the year 2015 to 2022 (Fig. 1). In 2022, there were about 6,829 road accidents, resulting in 7,713 deaths and 12,615 injuries [3]. The workforce in the country has suffered an economic loss of Tk 23,460 crore due to road accidents. If the property damage is included in the calculation, the loss would exceed 1.5% of the country's GDP [4]. The primary reason for road accidents is mainly due to humans driving vehicles recklessly. Reckless driving includes over-speeding, overtaking, and not following traffic laws. The most common factors that cause accidents include inexperienced drivers and risk-taking behaviors, drug or alcohol use, distracted driving, mobile phone use, and impaired driving due to a lack of law enforcement practices [5].

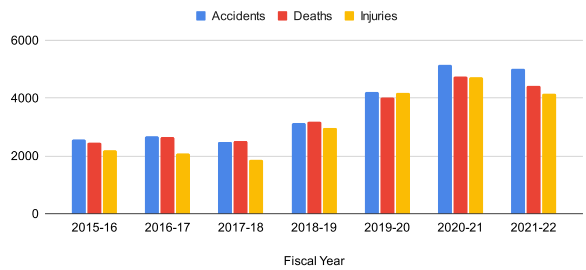

Fig. 1: Accidents, deaths, and injuries in Bangladesh according to BRTA's annual report 2021-22

According to the report of WHO, in order to provide safe transit for all road users, a system should be built to be tolerant of human error [1]. This is why the need for ADAS has become a dire necessity. ADAS is a human-computer interaction-based system that includes a number of technologies that can aid drivers in safe driving. The ADAS can warn & influence drivers against risky maneuvers, thus potentially saving thousands of lives [6].

This has motivated us to carry out this survey of the aspects, technologies, challenges, and possibilities of ADAS in the context of Bangladeshi roads. This work gives a clear, concise, and systematic overview of the technologies that may come in handy while implementing ADAS.

2. LITERATURE REVIEW

ADAS systems usually consist of object detection, object tracking, and vehicle behavior analysis functionalities with the added functionalities of Human-Machine Interface (HMI). Object detection tasks are typically done through the means of using sensors such as LiDAR, Radar, and CMOS RGB cameras. Recent advancements in deep learning methodologies have enabled researchers to develop more precise and robust real-time object detection solutions. Many crowd-sourced datasets and privately produced datasets have emerged over the years to tackle the challenge of training machine learning based object detection models. Various authors have published novel approaches to analyze the behavior of vehicles on the road based on the information composed by the vehicle, object detection, and tracking pipelines for autonomous driving and driver assisting systems.

Moujahid et al. [7] focus on the state-of-the-art machine learning techniques in advanced driving assistance systems (ADAS) as of 2018. Their work goes through a systematic analysis of the state-of-the-art ML algorithms and ADAS techniques separately before uniting them to determine the strengths and weaknesses, and the future of supervised, unsupervised, ensemble, and deep learning algorithms in reducing road accidents while combining them with ADAS. According to them, unsupervised learning algorithms are best suited for the preprocessing stage, and supervised learning works best in the case of object detection.

Di Feng et al. [8] discuss advancements in deep learning-based perception for autonomous driving from 2013 to 2019. They take into account the fusion of several types of sensors that are used to read environmental data around the vehicle. The problem of adding proper sensors to the proper situation has been addressed in their work. They go through a systematic review of the existing deep multi-modal object detection models and discuss the challenges. Intending to do so, they introduce the fusion of sensors, datasets, and background information required for object detection, along with semantic segmentation.

Ekim et al. [9] discuss the unsolved mysteries that cause autonomous driving to fail many times alongside a review of the available autonomous driving techniques, from the beginning of the autonomous driving history until 2019. Their work includes current challenges, top-level architectures of the system, emerging techniques, and core functionalities like localization, mapping, perception, planning, and human-computer interaction. Several real-world driving situations were plotted in their own simulator, and state-of-the-art algorithms were implemented and applied to them. The algorithms they reviewed show a significant drop in accuracy with the introduction to harder road conditions. The algorithms are still weak when it comes to facing harsh weather conditions. They also survey emerging trends like end-to-end driving approaches using deep learning, as well as the availability of datasets and software tools for autonomous driving development.

Mozaffari et al. [10] provide a comprehensive analysis of deep learning-based approaches for vehicle behavior prediction in autonomous driving applications up to the middle of 2020. They first discuss the challenges in this domain, including the complex interdependencies between vehicle behaviors, the influence of traffic rules and road geometry, and the multi-modal nature of vehicle trajectories. They categorize deep learning-based solutions based on input representation, output type, and prediction method, and they review the performance of several well-known models. Additionally, the authors identify research gaps and outline potential future research directions in this rapidly evolving field. They conclude their work with a decision that complex deep learning models work far better than any other strategies, which include multiple RNNs or the hybridization of RNNs. In the end, they discuss the gaps in the literature of those works and depict the future expanding possibilities.

Leon et. al. [11] show a literature review of two crucial aspects of autonomous driving until the beginning of 2021. Firstly, their focus is on tracking which includes detecting pedestrians, other vehicles, and objects on the road from sensors and other perceptor data. Secondly, they talk about trajectory prediction, which is predicting the motion of objects through sensors to know where they will be in the following time frames. They cover tracking methods based on deep neural networks as well as conventional approaches. For trajectory prediction, they discuss solutions based on deep neural networks, probabilistic models, and mixed approaches. Even though they do not mention any specific algorithms or methods that are definitively better than the others for tracking and trajectory prediction, their findings can serve as a valuable reference for assessing the computational trade-offs associated with different algorithmic choices.

De Jong et al. [12] discuss the state of sensors and sensor fusion technology in autonomous driving vehicles until the early part of 2021. They provide an end-to-end review of the hardware and software methods required for sensor fusion and object detection in autonomous driving. They summarize fusion technology, classified into three categories: low-level fusion, mid-level fusion, and high-level fusion. According to them, these techniques are very useful in generating suitable data to be fed to state-of-the-art algorithms such as SSD, YOLO, PointNet, and VoxelNet.

Abhishek et al. [13] provide a survey of the application of deep learning in object detection and perception of real-world scenes, covering developments up to 2021, in order to assist self-driving cars alongside classifying the existing algorithms. According to them, a combination of CNN and RNN works best as CNN extracts features better than any other models, and RNNs are great learners. They also depict that it is still hard for the assistive software to annotate the images without the help of a human being.

To summarize, the reviewed papers cover the state-of-the-art in machine learning and deep learning techniques for advanced driver assistance systems (ADAS) and autonomous driving up to 2021. They analyze the strengths and weaknesses of supervised, unsupervised, ensemble, and deep learning algorithms for tasks like object detection, behavior prediction, tracking, and sensor fusion. The papers highlight that unsupervised learning is useful for preprocessing, supervised learning works well for object detection, and complex deep learning models outperform other approaches for tasks like vehicle behavior prediction. However, the algorithms still struggle with challenging real-world conditions like bad weather. The reviews also discuss emerging trends like end-to-end driving using deep learning, available datasets, and software tools, and identify research gaps in this rapidly evolving field of autonomous driving. Given the fast pace of developments in this area, further review of more recent articles would be needed to capture the latest advancements.

Acknowledging the rapid progress in the field of advanced driver assistance systems (ADAS), the paper undertook a comparative analysis of leading-edge research articles from March 2021 to December 2023. The focus was on exploring techniques in environmental perception, object detection, object tracking, and data collection for ADAS applications. The analysis examined recent advances in sensors like radar, LiDAR, and cameras used for perception and detection, and evaluated the performance of object detection algorithms based on convolutional neural networks like YOLO, SSD, Mask R-CNN, and Faster R-CNN. The paper also reviewed object tracking methods, including correlation filters, Kalman filters, and Deep Sort, used to associate and maintain detected object identities over time. The analysis also covered object-tracking algorithms like Kalman filtering, particle filtering, and deep learning approaches that are particularly suitable for ADAS applications. Furthermore, the analysis delved into data collection, annotation, and management methods, including crowd-sourcing, simulation, and semi-automated approaches, that enable the development of robust ADAS systems. In summary, the review comprehensively evaluated the key enabling technologies for environmental perception, object detection, tracking, and data management in ADAS, while also highlighting the ongoing challenges and future research directions in this rapidly evolving field by addressing a set of research questions in mind.

The research questions (RQs) are:

- **RQ1.** What are the key advancements in sensor technologies?
- **RQ2.** How have machine learning techniques been utilized to enhance object detection and tracking?
- **RQ3.** To what extent do the currently available dataset address weather conditions, and capture real-world road scenarios and diverse vehicle types encountered?
- **RQ4.** How has the performance of these works been evaluated?
- **RQ5.** What might be the future of ADAS technology?

The following sections of this paper are organized as follows. Section 2 describes how the review was carried out. A generalized discussion of the selected papers is done in section 3. Section 4 broadly answers the above-mentioned research questions. Section 5 concludes the review by summarizing the entire study.

3. METHODOLOGY

According to the Systematic Literature Review (SLR), standards proposed by B. Kitchenham et al. [14], the review protocol follows six steps. Section I describes the initial two steps of the review protocol which are background and research questions.
The current section describes the other protocols.

3.1 Search Strategy

The search space for the paper collection includes numerous databases which include Google Scholar, IEEE, ACM, Springer, Scopus, Arxiv, MDPI, CVF, and Loughborough's Research Repository, etc. The search is performed using the following terms:

(ADAS OR assisted driving OR driving assistance)
AND (sensors OR preceptors)
AND (object detection OR obstacle detection)
AND (object tracking OR moving object detection OR obstacle tracking)
AND (machine learning OR deep learning OR computer vision OR image processing).

Using these criteria, 42 papers were found and after that, the following inclusion and exclusion criteria were utilized for further filtering.
The criteria that are followed while deciding whether to keep a paper or not under consideration are as follows.

1. Inclusion criteria
   - Papers that are published after March 2021 till December 2023
   - The studies should be focused on ADAS-related technologies
   - Contributions to the related field should be impactful
   - Included papers should be published in reputed journals or conferences
   - Papers should have higher citation
   - The papers must be written in English
2. Exclusion criteria
   - Papers that don't give a proper insight into the algorithms they used
   - Studies that fail to give a proper statistical analysis of the novel datasets
   - Any paper that is published before March 2021
   - Papers from unreliable publications
   - Papers that don't have a satisfactory number of citations and not a very recent publication

A total of 20 papers are selected after applying these criteria.

Table 1: General details of the selected papers

Year	Paper	Published in	Publication Type	Focused on
2023	Zhuyun et al. [15]	IEEE	Conference	Object Detection
	Yan et al. [16]	MDPI	Journal	Object Detection
	Reza et al. [17]	Elsevier	Journal	Behavior Prediction
2022	Yi-Nan et al. [18]	IEEE/CVF	Conference	Object Detection
	Wassim et al. [19]	IEEE/CVF	Conference	Object Tracking
	Meng et al. [20]	IEEE	Journal	Object Tracking
	Jianan et al. [21]	IEEE	Journal	Object Tracking
	Linhui et al. [22]	MDPI	Journal	Behavior Prediction
	Dian et al. [23]	IEEE/CVF	Conference	Behavior Prediction
	Christiaan et al. [24]	MDPI	Journal	Sensors
	Dong-Hee et al. [25]	NeurIPS	Conference	Object Detection

	Kaican et al. [26]	Springer	Conference	Dataset
	Yiming et al. [27]	IEEE	Journal	Dataset
2021	Yingfeng et al. [28]	IEEE	Journal	Object Detection
	Yuguang et al. [29]	Elsevier	Journal	Object Detection
	Chenxu et al. [30]	IEEE/CVF	Conference	Object Tracking
	Nikita et al. [31]	MDPI	Journal	Behavior Prediction
	. Ettinger et al. [32]	IEEE/CVF	Conference	Dataset
	Mao et al. [33]	NeurIPS	Conference	Dataset
	Xiao et al. [34]	IEEE	Conference	Dataset

Table 1 provides an overview of the selected papers in a structured manner.

3.2 Quality Assessment Checklist

In order to ensure the quality of the selected articles, a checklist where the phenomena taken into account were analysis of dataset, representation of results, identification of challenges, and insight of future work has been maintained.
The assessment is done in three categories, each having a different meaning for the phenomena which is shown in Table 2. The quality assessment of each paper is shown in Table 3.

3.3 Data Extraction Strategy

While going through the selected articles, the required information is extracted with the help of the following strategy. Firstly, by going through the abstract to get an overview of the work. Secondly, by looking for the dataset used in the work along with its statistical significance. Thirdly, by looking at the performance of their work and how they analyzed the results. Lastly, the limitations of those works and further improvement suggestions are taken into consideration.

Table 2: Categorization and definition of assessment criteria

	Assessment Criteria		
	Good	**Average**	**Poor**
Proper analysis of dataset	Has both description and tabular and / or pictorial representation	Has only written description	Has a summary of the entire dataset instead of a description
Representation of results	Has an easily interpretable tabular and pictorial representation	Has tabular representation only, causing difficulties while interpreting	Interpretation is difficult with the given table or diagram
Identification of challenges	Challenges are identified and the reasons are clearly described	Challenges identified only	Challenges not identified
Insight of future work	Future works include overcoming the challenges and more	Future works don't include overcoming the challenges	No insights into future works

Table 3: Quality assessment of the papers

Year	**Paper**	**Proper analysis of dataset**	**Representation of results**	**Identification of challenges**	**Insight of future work**
2023	Zhuyun et al. [15]	good	average	poor	poor
	Yan et al. [16]	good	good	average	poor
	Reza et al. [17]	good	good	good	good
2022	Yi-Nan et al. [18]	poor	good	poor	poor
	Wassim et al. [19]	good	good	average	average
	Meng et al. [20]	good	average	good	good
	Jianan et al. [21]	poor	good	good	good
	Linhui et al. [22]	good	average	good	good
	Dian et al. [23]	average	average	good	average
	Christiaan et al. [24]	average	average	average	good
	Dong-Hee et al. [25]	good	average	poor	poor
	Kaican et al. [26]	good	good	average	average
	Yiming et al. [27]	good	good	average	good

2021	Yingfeng et al. [28]	average	good	good	poor
	Yuguang et al. [29]	average	average	poor	average
	Chenxu et al. [30]	poor	average	average	poor
	Nikita et al. [31]	good	average	poor	good
	Ettinger et al. [32]	good	good	poor	poor
	Mao et al. [33]	good	average	average	average
	Xiao et al. [34]	good	good	average	average

4. GENERAL DISCUSSION OF THE SELECTED PAPERS

The selected papers provide valuable insights into the current trends and advancements in the field of ADAS. A common theme observed across the papers is the increasing emphasis on leveraging advanced sensor technologies and machine learning algorithms to enhance the perception capabilities of ADAS systems. The datasets they use are not always taken from the internet. Although there is an abundance of related datasets all over the internet, the reason behind the researchers being discouraged from using them is the fact that road conditions and traffic rules vary in different countries. Also, weather is a crucial factor in these cases. That is why most of these works try to implement their works on their own custom datasets. Data collected from cameras and sensors are fed to the algorithms they proposed just after splitting it into train-test-validation sets. The algorithms are supposed to do one or more of the following tasks: detect objects on roads that may be a car, a pedestrian, an animal, or any other object; keep track of these objects in case they are moving; anticipate the driving behavior for anomalous events. Once the models produce the outputs on the test or evaluation set, the performance is measured using several performance metrics namely, accuracy, precision, recall, f-score, Mean Average Precision (mAP), Average Precision (AP), Average Multi-Object Tracking Accuracy (AMOTA), driving score based on the application. The algorithms, which are novel or being used for the first time in this field or being properly tuned, employed here are cutting edge and produce significantly promising outputs while outperforming any other models of the past from the time of publication.
The chosen papers have been categorized into the following sections for better organization and clarity.

4.1 Perceptors

The ADAS technology requires the perception of the road condition which can be done using several input devices. These devices use ultrasound, infrared light, or cameras to input data from the environment and feed it to the system. The most suitable preceptors can be divided into the following categories based on the used technologies

Computer Vision based Technologies:
Computer vision is a technology that enables computers to see the world by extracting significant information from digital images or videos. Cameras play the role of sensors in this case. Cameras are cheaper when compared to other technologies, but the performance is highly dependent on the environment, especially in light conditions. The problem of low light exposure is resolved using infrared cameras, which are fairly expensive. Besides detecting incoming objects, such technologies can be used to detect road edges and lane markings [35], [36]. Edge detection algorithms employed on the data received from cameras can generate the outline shape of a car, empowering the detection algorithm [37]. 3D cameras, which are currently being used in the gaming industry [38], can show new horizons in the future, probably with the cost of computational resources.

Radar Technologies:
The simplest form of radar uses ultrasonic sensors to detect nearby objects. However, due to its short range, radio wave-based radars were introduced. Such devices attached to a vehicle can be used to determine the presence and relative velocity of objects that can prove to be dangerous for the driver. The biggest advantage that a radar provides is its robustness i.e., the ability to work under any environmental conditions. The drawbacks include being costlier than camera technologies and providing a ribald image of the surroundings. The FoV (Field of View) is also limited for radar technology. Adaptive cruise control (ACC) and side warning assist technologies are based on radar technology [39], [40]. The difference in emitted and reflected wave frequencies is used to determine the motion characteristics of any object [39].

LIDAR Technologies:
Light Detection and Ranging (LIDAR) is a technology that uses laser beams and creates a 3D, highly accurate image of the surroundings, giving the models the ability to determine anomalies of both the vehicle movement and the environment [41]. It is now dominating over vision-based technologies, because of its ability to work in low-light situations. LIDAR is now used in obstacle detection for vehicles [42] and is being introduced in the ACC domain [43]. Despite being a highly expensive technology, it is becoming a craze in the market.

Christiaan et al. [24] developed an Intra-vehicular Wireless Multimedia Sensor Network (IWMSN) where multiple sensors are used to establish a network among the vehicles running on the road. Their study uses smartphones for the purpose of communication, and sensors for the purpose of perception.

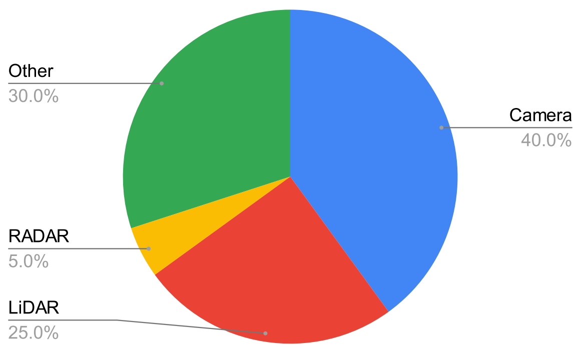

Fig. 2: Use of camera, LiDAR, RADAR, and other sensors in the selected papers

Fig. 2 shows a distribution of the use of sensors in the selected papers. Cameras are widely used, either as standalone devices or in conjunction with other sensors. The use of LiDAR sensors stand alone is being avoided these days.

4.2 Detection

The data perceived from the environment requires to be passed through some detection algorithms that will predict the environment around the vehicle. Zhuyun et al. [15] introduce RGB Event Fusion Network (RENet) for the purpose of Moving Object Detection (MOD) which is comparatively robust and works promisingly under harsh conditions. Yan et al. [16] introduce PMPF (Point-cloud multiple-pixel fusion) to be fused with SOTA technologies to provide a better outcome. It projects point cloud data to the image plane before being fed into the detectors using LiDAR technologies. Yi-Nan et al. [18] propose a pseudo-stereo 3D detection framework that generates three views from one image and constructs a 3D image. This is done through generating depth-level information. Dong-Hee et al. [25] revive RADAR-based object detection by introducing a 4D Radar Tensor (4DRT) in place of 3D Radar Tensor (3DRT) which overcomes the lack of providing elevation information. Applying Radar Tensor Network with Height (RTNH) and Tensor Network without Height (RTN), they get a significantly improved result. Yingfeng et al. [28] introduce YOLOv4-5D to detect moving objects where the final layer of CSPDarkNet-53, which is the backbone of the YOLOv4 network, is replaced with a deformable convolution network. YOLOv4-5D exceeds any of its predecessors in terms of performance. Yuguang et al. [29] propose StereoCenterNet (SC) which uses geometric information embedded in an image and provides both 3D and 2D bounding boxes around an object. They used an improved photometric alignment module which optimized the performance of their model.

4.3 Tracking

ADAS doesn't stop at only detecting objects, it needs to keep track of them as well. Jianan et al. [21] propose a random finite set-based tracker that adopts Poisson multi-Bernoulli filter using the global nearest neighbor (GNN-PMB) which works on data from LiDAR for the purpose of Multi-Object Tracking (MOT). Meng et al. [20] developed a pedestrian detection technique based on data fetched from thermal cameras. Their proposed algorithm detects a pedestrian at the location where the heatmap gives peak values. This is useful for high-speed applications. Wassim et al. [19] employ two SOTA technologies, namely TOOD [44] and VFNET [45] on thermal camera images to detect moving objects. Chenxu et al. [30] introduce SimTrack, which detects and tracks moving objects from raw point cloud data. It works for both 2D and 3D object detection. Maintaining a communication network among running vehicles can be a crucial step toward sensing the world outside the vehicle.

4.4 Prediction

Anomalous driving can be detected by analyzing the vehicle behavior. Works related to this aspect take into account data from simulators like CARLA, SUMO, Next Generation Simulation (NGSIM), or open-source high-resolution and low-resolution datasets. Reza et al. [17] propose a multi-task snapshot-stacked ensemble (MTSSE) deep neural network for detecting unusual driving behaviors. They divided driving scenarios into five critical tasks and then applied MTSSE to them. Dian et al. [23] introduce a system that collects data from all possible nearby vehicles and infers whether the driving pattern is normal or not. Linhui et al. [22] determine the behavior of vehicles using self-attention networks. It works based on a vehicle cluster of size five, among which, one is the ego-vehicle itself. Nikita et al. [31] focus on modeling vehicle behavior on urban, congested roads where lane changing is a common phenomenon. They used a game theory-based approach based on a two-player non-zero-sum game theory where they developed a decision-making model that relies on a dynamic non-cooperative game model.

4.5 Dataset

In the past, there was a multitude of datasets in the field of Advanced Driver Assistance Systems (ADAS), which played an important role in assisting research and development in autonomous driving. These datasets were specifically designed to offer a wide range of realistic and diverse driving scenarios, with the primary objective of enabling the evaluation of algorithms, training machine learning models, and establishing performance benchmarks for various autonomous driving tasks. Recent advancements have introduced new datasets that serve different purposes within the ADAS domain, further expanding the available resources in this field.

The WAYMO OPEN MOTION DATASET (WOMD), developed by Ettinger et al. [32], is a dataset targeted at creating motion forecasting models for autonomous driving systems. The dataset contains over 100,000 scenes, totaling more than 570 hours of data collected from six cities in the United States. It focuses on dynamic driving conditions like merges, unprotected turns, and other challenging situations. The dataset enables the creation of collaborative prediction models by giving precise labels for interacting objects. Each scene comes with high-quality 3D bounding boxes and maps. The dataset is made publicly available to the research community to advance motion forecasting research.

Mao et al. [33] introduce the ONCE (One Million Scenes) dataset, a massive and diverse dataset for autonomous driving. It is made up of 7 million camera photos and 1 million LiDAR scenes that were captured over 144 driving hours. The dataset is to help investigate self-supervised and semi-supervised techniques for 3D object detection and tackle the issue of data inadequacy in autonomous driving research. The ONCE dataset is described to offer superior data quality and diversity compared to other datasets. The dataset is publicly available.

Xiao et al. [34] introduce PandaSet, a dataset specifically designed for training autonomous driving perception algorithms. It is the first dataset generated by a high-precision, complete autonomous vehicle sensor kit and can be used commercially with no licensing fees. PandaSet contains information gathered from six cameras, a forward-facing long-range LiDAR, and a 360-degree mechanical spinning LiDAR. It offers 28 different types of labels for object categorization and 37 different types of labels for semantic segmentation throughout more than 100 scenarios, each lasting eight seconds. To advance 3D perception technologies for autonomous driving, the dataset provides baselines for a range of activities, including LiDAR point cloud segmentation and 3D object detection. It addresses a range of driving conditions and complex situations to improve the robustness of autonomous vehicles. PandaSet is an open-source dataset designed to aid research and development in the fields of autonomous driving and machine learning.

Kaican et al. [26] introduce a CODA dataset, which focuses on object detection in autonomous driving and specifically addresses the challenge of detecting uncommon objects and corner cases. The dataset contains 1500 real-world driving scenes with carefully selected corner cases from more than 30 object categories. Existing object detection algorithms trained on large-scale autonomous driving datasets perform poorly on CODA, pointing out the need for better detection capabilities. CODA's goal is to promote research on reliable detection for real-world autonomous driving. The dataset can be found on their GitHub page.

Yiming et al. [27] developed V2X-Sim, a large simulated dataset for collaborative perception in autonomous driving. The datasets contain multi-agent sensor recordings that allow for collaborative perception, multi-modality perception, and multiple ground truths for a variety of perception tasks. There is also an open-source benchmark for cutting-edge collaborative perception algorithms. The idea is to encourage collaborative perception research before realistic datasets are generally available. They published the datasets on GitHub.
These datasets address various aspects of autonomous driving, including motion forecasting, object detection, perception algorithms, road event detection, collaborative perception, logical constraints, and weather conditions. Table 4 shows the overall summary of the selected papers.

Table 4: Summary of the selected papers

Year	Paper	Data Collection Technique	Technique/Algorithm used for detection/tracking	Dataset	Evaluation metrics
2023	Zhuyun et al. [15]	Camera	RENet	DSEC-MOD	mAP
	Yan et al. [16]	LiDAR, Camera	PMPF	KITTI	mAP
	Reza et al. [17]	-	MTSSE	LVD	f-score
2022	Yi-Nan et al. [18]	LiDAR, Camera	LIGA-Stereo	KITTI-3D	AP
	Wassim et al. [19]	Thermal Sensor, Infrared Camera, RGB Camera	VFNET	City Scene RGB-Thermal MOT Dataset, FLIR ADAS Dataset	AMOTA
	Meng et al. [20]	Thermal IR Camera	Thermal Infrared Single-Pedestrian Tracking	PTB-TIR, Own Dataset	PrecisionScore
	Jianan et al. [21]	LiDAR, Camera	GNN-PMB	nuScenes	AMOTA
	Linhui et al. [22]	-	VC-Attention	NGSIM	Accuracy
	Dian et al. [23]	-	Learning from all Vehicles	CARLA	Driving Score
	Christiaan et al. [24]	-	IWMSN	-	-
	Dong-Hee et al. [25]	Radar	RTNH, RTN	KAIST-Radar	AP
	Kaican et al. [26]	LiDAR, Camera	R-CNN, DETR, and ORE	CODA	-
	Yiming et al. [27]	LiDAR, Camera	SOTA algorithm	V2X-Sim	HOTA
2021	Yingfeng et al. [28]	Camera	YOLOv4-5D	BDD and KITTI	mAP
	Yuguang et al. [29]	LiDAR, Camera	SC	KITTI	AP
	Chenxu et al. [30]	LiDAR	SimTrack	nuScenes and Waymo	AMOTA
	Nikita et al. [31]	-	Game Theory	SUMO Simulator	Accuracy
	Ettinger et al. [32]	LiDAR, Camera	Data Mining	WOMD	-
	Mao et al. [33]	LiDAR, Camera	Supervised Learning	ONCE	-
	Xiao et al. [34]	LiDAR, Camera	Sensor Fusion	PandaSet	-

5. ANSWERS TO THE RESEARCH QUESTIONS (RQS)

RQ1. What are the key advancements in sensor technologies?

The key advancements in sensor technologies are as follows:

- LiDAR systems have undergone a remarkable transformation in recent times. They have transitioned from being expensive and bulky to becoming more compact, and affordable, and delivering improved performance.
- Camera technologies are getting upgraded with increased resolution and the ability to work under extreme weather and lighting conditions
- The most crucial advantage in sensor technologies is the use of fusion where multiple sensors are fused together to get more robust and useful information for the algorithms to use.

Fig. 3 demonstrates a clear upward trend in the adoption of cameras. Furthermore, there has been a notable rise in the utilization of mixed sensor configurations, highlighting the complementary nature of different sensor modalities. Specifically, the integration of LiDAR sensors with other sensor types has become a common practice.

Among the sensor technologies mentioned in this section, cameras are the most budget-friendly which leads to its upward trend. Resolution, lighting, and weather conditions affect the performance of cameras. This is where LiDAR sensors come into action with their lighting and weather-independent performance. One drawback of installing LiDAR sensors have a higher cost compared to cameras. Due to its better understanding of the environment, mixing sensor technologies are most widely used in the selected time frame.

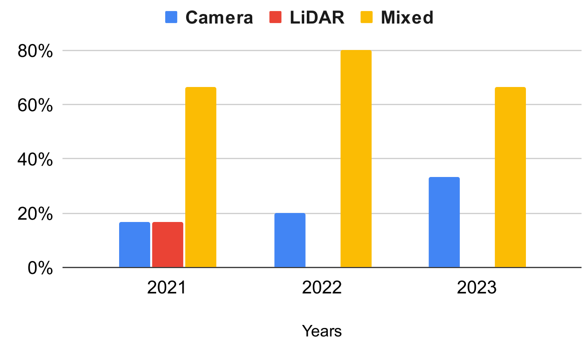

Fig. 3: Use of sensors in the selected papers

RQ2. How have machine learning techniques been utilized to enhance object detection and tracking?

Machine learning techniques, especially the ones belonging to the deep learning field have gained significant popularity for object detection and tracking in Advanced Driver Assistance Systems (ADAS). Researchers tend to carry out their research employing a diversity of algorithms in both applications.

In the case of object detection RENet [15], [16], YOLOv4-5D [28], [29], [25] and LIGA-Sterio [18] are some of the novel algorithms. Among these, YOLOv4-5D shows the best performance in terms of mAP (87.02%) and SC outperforms the others in terms of AP (47.44%). Fig. 4 and Fig. 5 show a comparison of the works in terms of mAP and AP.

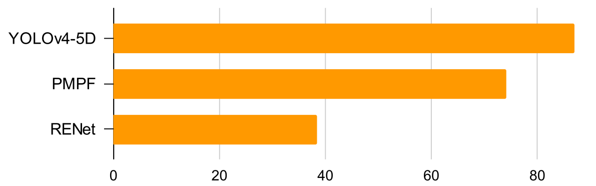

Fig. 4: Performance comparison of detection algorithms in terms of mAP.

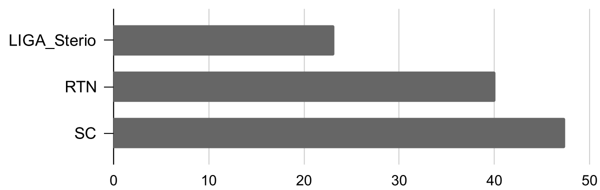

Fig. 5: Performance comparison of detection algorithms in terms of AP.

When it comes to object tracking MTSSE [17], VFNET [19], Thermal Infrared Tracking [20], GNN-PMB [21], VC-Attention [22], and SimTrack [30] algorithms are some of the novel algorithms. VFNET has the highest AMOTA (85) whereas MTSSE and Thermal Infrared Tracking display the maximum confusion matrix-based score (98). Fig. 6 and Fig. 7 show a comparison of the works in terms of AMOTA and confusion matrix-based score.

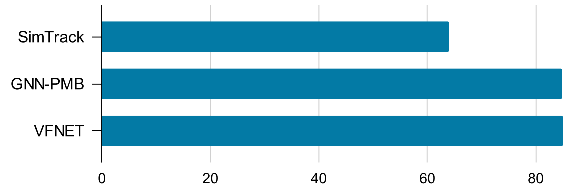

Fig. 6: Performance comparison of tracking algorithms in terms of AMOTA.

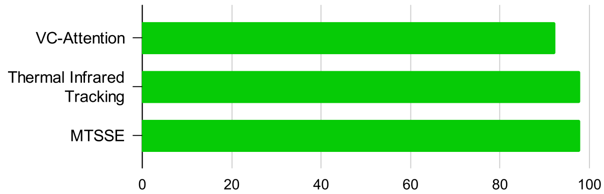

Fig. 7: Performance comparison of tracking algorithms in terms of confusion matrix-based metrics.

Algorithms other than machine learning, for example Learning from all Vehicles [23] and Game Theory based approaches [31]. are also playing a vital role in this field.

RQ3. To what extent do the datasets address weather conditions, capture real-world road scenarios and diverse vehicle types encountered?

The chosen papers explore a wide array of datasets that exhibited distinctive attributes and provided valuable insights. These datasets encompass diverse types such as image datasets, text corpora, and real-world sensor data.

These datasets are meticulously collected under various weather conditions, ensuring a comprehensive representation of real-world scenarios. The weather conditions span a range of environments, including but not limited to sunny, rainy, foggy, and snowy conditions. Table 5 illustrates the specific weather conditions and corresponding dataset details. The examination of the datasets revealed a strong emphasis on capturing data in Sunny, Rainy, and Foggy weather conditions. However, there was a noticeable scarcity of datasets that also considered Night-Time and Snowy conditions. Notably, stormy weather conditions were conspicuously absent from the datasets, indicating a lack of representation for such challenging weather scenarios. Fig. 8 gives an illustration of the observation.

Table 5: Weather conditions addressed in the datasets

Paper	Night Time	Sunny	Cloudy	Rainy	Foggy	Snowy	Stormy
Yingfeng et al. [28], Yan et al. [16], Yi-Nan et al. [18], Yuguang et al. [29]	-	Yes	Yes	Yes	-	-	-
Yingfeng et al. [28]	-	Yes	Yes	Yes	Yes	-	-
Zhuyun et al. [15]	-	-	-	-	-	-	-
Dong-Hee et al. [25]	-	-	-	Yes	Yes	Yes	-
Chenxu et al. [30], Jianan et al. [21]	-	Yes	Yes	Yes	Yes	-	-
Chenxu et al. [30]	-	Yes	-	Yes	Yes	-	-
Wassim et al. [19]	-	-	-	-	-	-	-
Christiaan et al. [24]	Yes	Yes	-	Yes	Yes	Yes	-
Linhui et al. [22]	-	-	-	-	-	-	-
Ettinger et al. [32]	-	-	-	-	-	-	-
Mao et al. [33]	-	Yes	Yes	Yes	Yes	-	-
Xiao et al. [34]	-	Yes	Yes	Yes	Yes	-	-
Kaican et al. [26]	Yes	Yes	Yes	Yes	Yes	-	-
Yiming et al. [27]	-	-	-	-	-	-	-

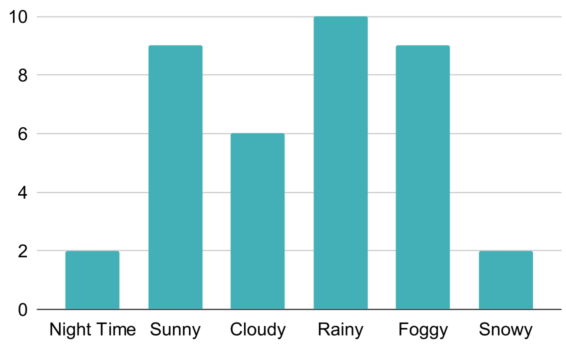

Fig. 8: Distribution of weather conditions in the datasets

These datasets are carefully collected to encompass a diverse array of real-world road scenarios. Table 6 outlines the specific road scenarios and their corresponding dataset details. The majority of the datasets were focused on obtaining data from urban roads and highways. There was, however, a noteworthy lack of datasets that accurately reflected circumstances characterized by Heavy Traffic. This discovery highlights the importance of dense traffic datasets, as they bring unique problems and complexity that require special consideration in the creation and assessment of traffic-related systems and algorithms. The distribution of road scenarios is shown in Fig. 9.

Table 6: Road conditions addressed in the datasets

Paper	Urban Roads	Suburban Roads	Highway	Rural roads	Heavy Traffic
Yingfeng et al. [28], Yan et al. [16], Yi-Nan et al. [18], Yuguang et al. [29]	Yes	-	Yes	-	-
Yingfeng et al. [28]	Yes	-	Yes	Yes	-
Zhuyun et al. [15]	Yes	-	Yes	-	-
Dong-Hee et al. [25]	Yes	Yes	Yes	-	-
Chenxu et al. [30], Jianan et al. [21]	Yes	Yes	Yes	-	-
Chenxu et al. [30]	Yes	Yes	Yes	-	-
Wassim et al. [19]	Yes	-	-	-	-
Christiaan et al. [24]	Yes	-	Yes	Yes	Yes
Linhui et al. [22]	-	-	-	-	-
Ettinger et al. [32]	Yes	-	-	-	-
Mao et al. [33]	Yes	Yes	Yes	-	-
Xiao et al. [34]	Yes	Yes	Yes	-	Yes
Kaican et al. [26]	Yes	Yes	Yes	Yes	-
Yiming et al. [27]	-	-	-	-	-

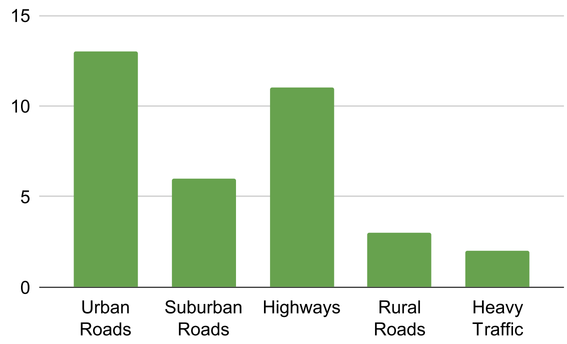

Fig. 9: Distribution of road conditions in the datasets

Achieving precise and reliable vehicle detection on the road is of utmost importance, emphasizing the need for a dataset that encompasses a wide variety of vehicle types. This diversity is essential in capturing the nuances and characteristics of different vehicles, enabling robust detection algorithms to handle diverse real-world scenarios.

Table 7 presents the specific vehicle types and their corresponding dataset details. The distribution shown in Fig. 10 depicts that the majority of the datasets examined centered on vehicles regularly observed on roads, such as cars, trucks, buses, and motorbikes. However, there was a distinct lack of somewhat different vehicle types, such as rickshaws or CNG vehicles, which are common in Asian nations such as India and Bangladesh. The ADAS field has yet to properly contemplate including these specific vehicle classifications, which contribute significantly to the traffic landscape in these regions. Addressing this gap by including a variety of vehicle types will improve the application and efficacy of ADAS technology in real-world circumstances, particularly in Asian nations where these vehicles play an important role.

Table 7: Vehicle types considered in the datasets

Paper	Car	Truck	Bus	MotorCycle	Bicycle	Van
Yingfeng et al. [28], Yan et al. [16], Yi-Nan et al. [18], Yuguang et al. [29]	Yes	Yes	Yes	Yes	Yes	Yes
Yingfeng et al. [28]	Yes	Yes	Yes	Yes	-	-
Zhuyun et al. [15]	Yes	Yes	Yes	Yes	Yes	-
Dong-Hee et al. [25]	Yes	Yes	Yes	Yes	Yes	-
Chenxu et al. [30], Jianan et al. [21]	Yes	Yes	-	-	Yes	-
Chenxu et al. [30]	Yes	Yes	-	Yes	Yes	-
Wassim et al. [19]	Yes	-	-	-	-	-
Christiaan et al. [24]	Yes	Yes	Yes	Yes	Yes	Yes
Linhui et al. [22]	-	-	-	-	-	-
Ettinger et al. [32]	Yes	Yes	Yes	Yes	Yes	-
Mao et al. [33]	Yes	Yes	Yes	Yes	Yes	-
Xiao et al. [34]	-	-	-	-	-	-
Kaican et al. [26]	Yes	Yes	Yes	Yes	Yes	Yes
Yiming et al. [27]	-	-	-	-	-	-

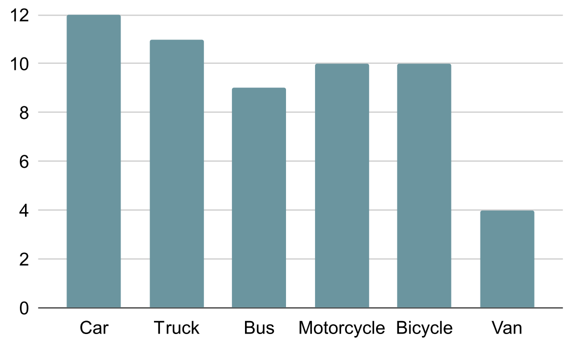

Fig. 10: Distribution of vehicle types in the datasets

RQ4. How has the performance of these works been evaluated?

we can evaluate the performance of these works by using the following metrics.

1. **Average Precision (AP):** Average Precision is a popular metric for evaluating object detection. It calculates the precision and recall at various intersection-over-union (IoU) criteria to determine the accuracy of object detection. The area under the precision-recall curve is then used to calculate the AP.
2. **Average Multi-Object Tracking Accuracy (AMOTA):** Tracking accuracy assesses a tracking algorithm's ability to properly track objects over time. Metrics like tracking precision (the average distance between anticipated and ground truth object positions) and tracking recall (the proportion of accurately tracked frames) can be used to assess it.
3. **Mean Average Precision (mAP):** The mean of the AP values calculated at various IoU thresholds is known as mAP. It provides an overall assessment of the detection performance across different object classes.
4. **Confusion matrix-based metrics:** Certain performance metrics such as accuracy, precision-score, and f-score are also used. Accuracy measures the ability of a model by taking the ratio of total correct predictions to total instances. The precision-score refers to the accuracy of positive predictions. F-score makes an assessment which balances the precision-recall trade-off.
5. **Custom Metrics:** Some researchers tend to use customized performance metrics for the evaluation of

their work. For example, driving score [23], and HOTA [27].

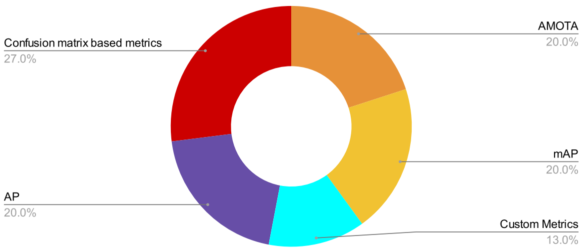

Fig. 11: Performance metrics used in the selected papers

The distribution of the usage of different metrics is shown in Fig. 11. As the use of confusion matrix-based metrics as the performance measure is the highest among all, it can be concluded that mAP is the best suited metric for the evaluation of the ADAS systems.

RQ5. What might be the future of the ADAS technology?
The current trends of the ADAS technology show that it is going to lead us to a future where more accurate assistance will be provided. The future of the ADAS technology can be as follows:

- Since the perceptors will get significant upgrades in the future, it is highly likely that the fusion among 3D cameras, LiDARs, RADARs, and other wireless sensors in a single vehicle will be applied. This will lead to a significant increase in the quality and quantity of information to be fed to the detectors or trackers.
- With the improvement of performance in modern-day personal computers, using high resource-consuming simulators for ordinary people will not be an issue anymore. The usage of simulators in the case of ADAS will increase.
- Ensembling transferred models fused with certain algorithms may be employed leading to a significant improvement in the performance of the ADAS system.

6. CONCLUSION

This review paper has given a clear and concise insight into 20 systematically selected papers published within the time frame of 2021 to December 2023. The study aims to assist researchers who are working in the field of ADAS in finding what they are looking for. A total of five questions about the growth of the field of sensors, the contribution of machine learning algorithms in detecting and tracking objects, the quality of the available datasets, performance evaluation, and possible future trends have been answered. The conclusion that can be drawn from going through papers related to sensor technologies is that using a single sensor for the purpose of assisting drivers is severely challenging. As a result, the use of multiple sensors to keep track of various anomalous situations on the roads is becoming increasingly popular. Anomalous road conditions are not often encountered. Also, the road conditions vary from locality to locality. By this means, it is nearly impossible to form a dataset containing all scenarios and it leads to the fact that the datasets used in the relevant studies each lack the coverage of all possible conditions leading to the scope of the algorithms to make significant errors in some corner case scenarios. The machine learning and deep learning algorithms used in the selected articles are conventional algorithms as well as customized algorithms. Transfer learning has been the most widely used for the purpose of detecting objects on roads and later keeping track of them. Confusion matrix-based performance metrics i.e., accuracy, precision, and f-score are the most widely used means of evaluating the models. Looking into the shortcomings of the selected studies, it is found that a real-time system is not properly into action yet.

Upon inspection of the changes in several aspects of ADAS, a number of tendencies can be projected. With the advancement of technology, the perceptors are attaining more precise perception capabilities. As a result, integrating multiple of these together will facilitate the creation of datasets which may lead to a more accurate assistive system. Computing devices are getting swifter and being miniaturized over the course of time. Installing these high-performance compact devices on the vehicles will make the overall assistive systems remarkably faster and as a result the real-time platform may be established. Ensemble learning is witnessed to be on the list of rising trends in the field of artificial intelligence. Plugging in notably cutting-edge algorithms to formulate a system more robust in nature can also be taken into account.

This study can be enhanced down the road through the study of more SOTA articles involving ADAS at regular intervals. A compilation of findings from studies related to autonomous driving, an allied domain of ADAS, can be included as well. Also, the advancements in preceptor technologies can be reviewed in a separate article. The recurrent studies can help researchers to carry out their research with less effort to put up against searching articles related to their cause.

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